doi: 10.14355/spr.2015.04.006

Complex Wavelet Package Image Restoration to Support Operational Application

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Abstract

Operational application image restoration method with high quality, high efficiency and robustness is presented, for high resolution optical remote sensing satellite. Firstly, images are block segmented according to CCD characteristics, and periodic plus smooth decomposition and dequantization are processed. Then, noise and MTF curves are estimated adaptively using spectrum masking for taking into account the on-orbit dynamical imaging properties. Thirdly, deconvolution filters are optimized in different frequency in order to balance among the blurring, aliasing, noise and ringing effects, based on known noise and MTF's shape and value. Fourthly, adaptive threshold to color noise are treated rapidly utilizing the shift invariance and the direction selectivity of complex wavelet package(CWP) unique features. Fifthly the weak texture regions are reserved. Experiments shows that the method can significantly improve image sharpness, with universality adaption, and has a good operational application prospects.

Keywords

Image Restoration; Remote Sensing Satellite; Complex Wavelet Package; Operational Application; Universality Adaption

Introduction

In order to meet the requirement of both low-cost and high imaging quality, the trade-offs design between spaceborne optical remote sensing imaging system and ground processing system is mostly used. The high resolution optical remote sensor mainly uses relatively small aperture to realize a long focal length, together with TDICCD detector and highly integrated low noise circuit to achieve a high signal to noise ratio (SNR). However, the decreased aperture and the increased TDI stages will theoretically caused a decrease of on-orbit dynamical system MTF. Therefore, it is necessary to restore image efficiently on the ground with matching on-orbit imaging characteristics, so as to guarantee the high quality of the final imagery products (Philippe,2002).

However, due to resolution improvement, remote imagery will include richer texture details, and on-orbit dynamical imaging characteristics are more sensitive to scene change. Furthermore, the volume of remote sensing data is huge, therefore, the restoration methods with high quality and efficiency, strong universality will meet many challenges. The French Centre National d'Études Spatiales (CNES) has been a lot of research work on the remote sensing image adaptive restoration, whose COWPATH system and DEPA system are both the typical image restoration system based on CWP domain (Jalobeanu, 2002).

The purpose of this paper is to promote the operational application with high adaption, and it will play a vital role for the performance optimization of optical remote sensing satellite imaging system.

CWP Transform

Complex wavelet was first presented by the British mathematician Nick Kingsbury (Kingsbury, 2001). Dual Rree Complex Wavelet has been widely used in image and signal processing. The CWP not only has the perfect reconstruction property and the calculation efficiency of the real wavelet coefficients, but also has approximate shift invariance which the real wavelet coefficients don't have. More importantly, through four times data redundancy, the complex wavelet gets the more abundant direction selection characteristics, especially in the high frequency portion. In the same frequency band, the real wavelet produce three sub bands, while the CWP produce six sub bands. Therefore the complex wavelet coefficients can improve the accuracy of image decomposition and

reconstruction, at the same time it can retain the details of image. As shown in FIG.1:

The first layer decomposition of the CWP image decomposition is according to the Kingsbury dual tree complex wavelet filter structure. Beginning from the second layer decomposition, the 4 branches obtained from the decomposition of the first layer (four trees) should be iterative decomposition.

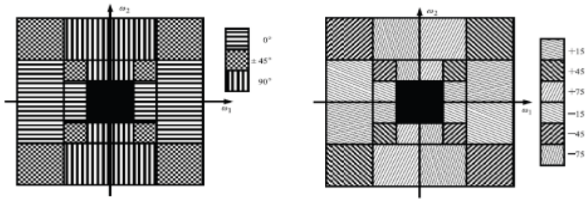

FIG. 1 REAL WAVELET COEFFICIENTS (LEFT)AND COMPLEX WAVELET COEFFICIENTS (RIGHT)

Adaptive Image Restoration Based on CWPT

Boundary Ringing Suppression Based on Decomposition and Dequantization

The ringing effect generally exists in image restoration, which seriously affects the visual quality. In order to meet large formate business running needs, block segmentation strategies are used. Here, the number of pixels in block unit (512*512) corresponding to each CCD port (for example 512 pixel) will be as the basic processing unit.

1) P+S Decomposition

After all block images processed, a large image will be synthetic, and mosaic area has obvious block effect. To eliminate the boundary ring, the block image will be decomposed into periodic signal P and smooth signal S, where P is the basic signal, the smoothing signal is less in the image of internal energy.

Suppose U express the image with size of $M \times N$, where $U \in R^{\Omega}$, $\Omega = \{0,\ldots,M-1\} \times \{0,\ldots,N-1\}$, for $\forall (q,r) \in \Omega \setminus (0,0)$, there are the following formula:

$$per(u)\hat{u}(q,r) = \hat{u}(q,r) - \frac{\hat{v}(q,r)}{2\cos(2\pi q/M) + 2\cos(2\pi r/N) - 4},\ per(u)(0,0) = \hat{u}(0,0),\ v = v_1 + v_2, \text{ for } \forall (x,y) \in \Omega:$$

$$v_1(x,y) = \begin{cases} u(M-1-x,y) - u(x,y) & x = 0 or x = M-1 \\ 0 \quad others & \end{cases}$$

$$v_2(x,y) = \begin{cases} u(x,N-1-y) - u(x,y) & y = 0 or y = N-1 \\ 0 \quad others & \end{cases}$$

Periodic signal P is expressed as $P = per(u)$, and the smoothing signal is expressed as $S = U - P$.

2) Dequantization Processing

To reduce the aliasing effect caused by undersampling and retain the texture direction, and effectively eliminate the influence of residual error by non-uniformity correction, P can obtain the periodic signal P′ by the dequantization process, where size of P′ is $M \times N$, $M' = \lfloor M/2 \rfloor$, $N' = \lfloor N/2 \rfloor$.

$$T_x = \exp\left[-i * pi * \left(x\%M - M'\right)/M\right]$$
$$T_y = \exp\left[-i * pi * \left(y\%N - N'\right)/N\right]$$

Where, $x \in [M', M'+M], y \in [N', N'+N]$

P′ by the quantization process is expressed as:

$$P' = R\left\{IFFT\left[FFT(U) \otimes (T_y{}' \otimes T_x)\right]\right\}$$

MTF and Noise Estimate with Spectrum Masking

To restore of blur and noise image automatically, the MTF and noise will be estimated parameters caused by image degradation. Suppose that the satellite image Y is obtained by the blurred image H*X plus gauss white noise N, $Y = H * X + N$, where H is the convolution kernel and X is the original image.

The variance σ^2 of noise N can be accurately estimated by image Y, and the blurred function of ideal image X with the convolution kernel H can be equivalent to the multiplying effect with MTF.

1) Noise Estimation

The noise mainly includes two parts, one part is the shot noise associated with the signal magnitude which satisfies the poisson distribution (the coefficient B is proportional to the signal). Another part is white noise A of Gauss distribution independent of signal. Noise variance: $\sigma^2(s) = A + B * s(x, y)$

Through the spectrum masking of the high frequency region of the multiple non-overlapping sub block images, the Gauss distribution white noise which is signal independent and the Poisson distribution shot noise which is signal dependent can be obtained. And at last get the SNR curve through linear fitting analysis.

2) MTF Estimation

In frequency domain, MTF can be expressed as component multiply of atmospheric, optical system, detector, platform , shown in ref.(Jalobeanu,2002):

$$\mathrm{MTF_0} = \mathrm{MTF_{atm}} * \mathrm{MTF_{opt}} * \mathrm{MTF_{mot}} * \mathrm{MTF_{sen}}$$

MTF curve obtained through theory computation or actual prediction has the main part, which is relatively stable. The dynamical disturbance part is difficult to test but has smaller proportion, which is instable and can be obtained by adaptive prediction. For these uncertain factors, the effects are expressed by a non isotropic Gauss function:

$$\mathrm{MTF} = \mathrm{MTF_0} * \exp(-\alpha_0 \mathrm{u}^2 - \alpha_1 \mathrm{v}^2)$$

Without typical edge or point target, the MTF curve can be obtained through the low frequency mask adaptivly(Jalobeanu,2002). The parameters α_0 , α_1 can be obtained throught the maximum likelihood estimation.

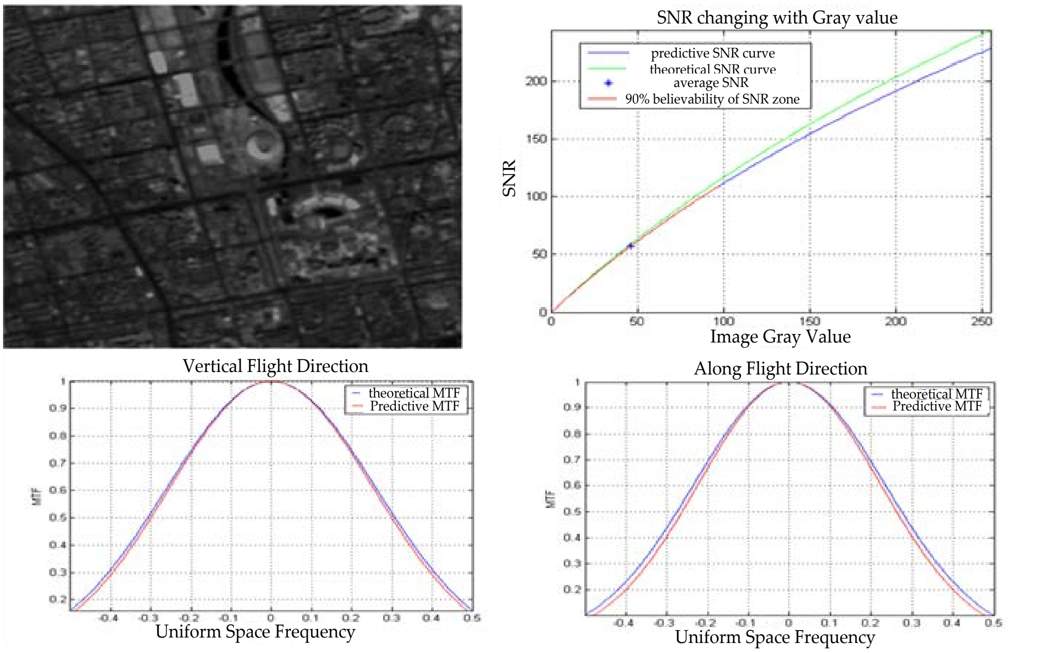

FIG. 2 SIMULATION RESULTS OF SNR AND MTF CURVE

3) Comparation of Predictive and Theoretical Value

The satellite images acquired on-orbit as the simulation source, and firstly the image can be blurred with MTF convolution, and then resampling, then add the shot noise satisfied with the Poisson distribution, and furthermore white noise with the Gauss distribution, at last export the degraded images. Comparative analysis of predictive and theoretical value is carried out, and the results show that the estimated curve and the theoretical curve are very close. Experiment results show that the precision of MTF and noise estimation is better than 90%. As shown in FIG.2.

Deconvolution Filter Optimization Design

Dynamical MTF value in high frequency is relatively small, which may cause significant amplification of noise when divided by MTF directly. Furthermore, the aliasing effect caused by under sampling, the false information will be magnified (Jalobeanu, 2003). To effectively suppress these phenomenons, comprehensive balance by considering blur, aliasing, noise and ringing, the deconvolution filter is optimized in different frequency. For example, the maxium MTF value increases about 2.5 times (around the 0.4X sampling frequency point), and the MTF value at Nyquist frequency increases about 2 times (around the 0.5 X sampling frequency point), shown in FIG.3.

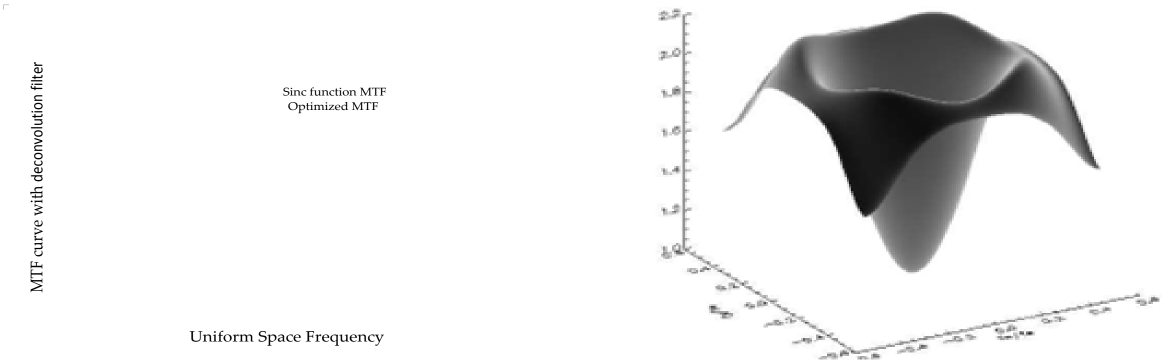

FIG.3 DECONVOLUTION FILTER IN DIFFERENT FREQUENCY

Color Noise Adaptive Processing

Using the estimated MTF curves, in frequency domain can be no regularized deconvolution, by which the high noise gain will degrade image. Suppose after the CWP domain decomposition, the color noise of each sub frequency band is independent of Gauss white noise, ant the noise variance estimation of σ_k^2 can be estimated according to the formula: $\sigma_k^2=\sigma^2\sum_{i,j}\left|F(W_k)_{i,j}/F(H)_{i,j}\right|^2$.

After the completion of the maximum likelihood estimation, soft threshold is used to filter noise for each sub frequency band. Finally the coefficients of CWP domain is inverse transformed into spatial domain, to realize the remote sensing image restoration.

Because of the shift invariant, considering the more directional characteristics, and maintaining a certain complexity, compared with other algorithms, it has the advantages of faster, rotation invariant, enhancing the image details and reserving the texture direction, therefore, the quality of image restoration is much better than others (Latry,2012).

According to the statistical distribution characteristics of the image, the adaptive soft threshold denoising method can effectively keep the useful information, and remove the useless noise information. Thus the image restoration processing can improve the MTF, while not magnify image noise (mainly white noise), and ensure the high SNR of image.

Adaptive Retains of Weak Texture Region

There are relatively few effective information in weak texture region (Liu,2013), and the various noise dominates

the main role, such as background noise, fixed pattern noise, stray noise, white noise, etc. To ensure that the noise was not significantly enlarged, it is necessary to retain weak texture region adaptive, so it will not bring a large false information. FIG.5 is the adaptive detection result.

Experimental Results

The panchromatic images of city area of ZY02C-HR, SJ-9A, GF-1 are selected. To evaluate the image quality, the image sharpness index without reference is used, which can balance the blur, aliasing, noise and ringing, and can evaluate the image quality objectively. As shown in TABLE1 and FIG.6, the restoration results show that the method can more significantly improve the image sharpness, and the noise can be effectively suppressed.

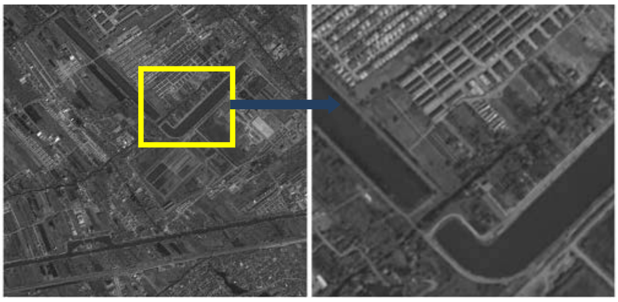

FIG. 4 AFTER COLOR NOISE REMOVING

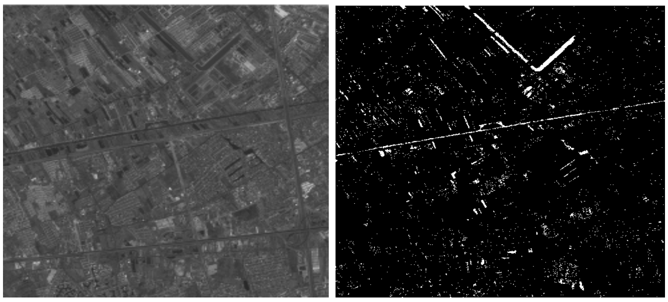

FIG.5 ADAPTIVE DETECTION OF WEAK TEXTURE

TABLE 1. SHARPNESS INDEX BEFORE AND AFTER RESTORATION

sharpness index	original	restoration	improved ratio
ZY02C-HR	8719.8	11041.2	1.27
SJ-9A	1304.9	1527.3	1.17
GF-1	6068.7	7338.9	1.21

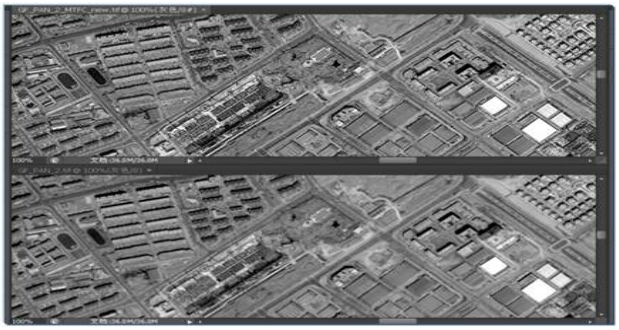

FIG. 6 ORIGNAL AND RESTORATION IMAGE OF GF-1

Conclusion

Aiming at the difficulties of restoration methods for high resolution satellite image with high quality, high efficiency, strong universality, this paper does the key technology research, such as block segmentation for large images, high precision adaptive estimation for MTF and noise parameters, optimization design of deconvolution filter, adaptive color noise processing, texture details preserving. The experimental results show that this method can significantly improve the satellite image quality, which has the capability of rapid, high-volume operation processing.

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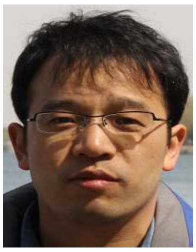

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